

Impact of Neuron Count on Prediction Capabilities in PINNs: Integrating Physics and Data

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1 Introduction

Physics-Informed Neural Networks (PINNs) meld data-driven learning with the incorporation of physical principles [2]. This report emphasizes how neuron count, specifically 64 versus 128 neurons, affects the prediction capabilities of PINNs for wind angle data, considering the integration of physics.

2 The Role of Physics in PINNs

Incorporating physical principles into neural networks ensures that the predictions adhere to established physical laws, even in regions of the input space where data might be sparse [2]. This integration can lead to more accurate and generalizable predictions, especially for tasks involving physical phenomena like wind patterns.

3 Prediction Capabilities with 64 Neurons

3.1 Generalization and Robustness

A smaller network with 64 neurons might generalize better to unseen data, especially if the dataset size is limited [1]. By integrating physical laws, the predictions can be made more robust, ensuring that even with fewer neurons, the network doesn't stray from physically plausible outputs.

3.2 Reaction to Noise

With fewer parameters, smaller networks can be less sensitive to noise [3]. In the context of wind data, which can contain noise, the combination of physics and a compact network might yield stable predictions.

3.3 Limitations in Complex Scenario Predictions

Despite the advantages, a 64-neuron network might struggle with intricate wind patterns. While physical laws ensure plausibility, the model might lack the flexibility to capture all complexities, leading to potential inaccuracies [1].

4 Prediction Capabilities with 128 Neurons

4.1 Handling of Complex Scenarios

The higher capacity of a 128-neuron network allows it to represent intricate patterns effectively [1]. When combined with physical constraints, this can result in accurate predictions even in complex wind scenarios.

4.2 Fine-grained Predictions

The increased capacity can yield more detailed predictions, capturing subtle nuances in wind patterns. The integration of physics ensures that these detailed predictions remain physically plausible [2].

4.3 Risk of Over-sensitivity to Noise

Larger networks can be more sensitive to noise [3]. However, by incorporating physical principles, this sensitivity can be mitigated to an extent, ensuring predictions remain within physically acceptable bounds.

5 Conclusion

The neuron count in a PINN significantly influences its prediction capabilities, with the integration of physics playing a pivotal role in ensuring physically plausible outputs. While 64 neurons offer robustness and generalizability, 128 neurons provide the flexibility needed for complex scenarios. The choice of neuron count should be

guided by the intricacies of the wind data and the importance of ensuring physically consistent predictions. In any case, experimenting with different neuron counts is a worthwhile endeavor in and of itself as it allows for a deeper understanding between the interplay of neuron count and predicative abilities of the PINN.

References

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